Automatic Disaggregation of Total Electrical Load from Non-intrusive Appliance Load Monitoring

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Outline

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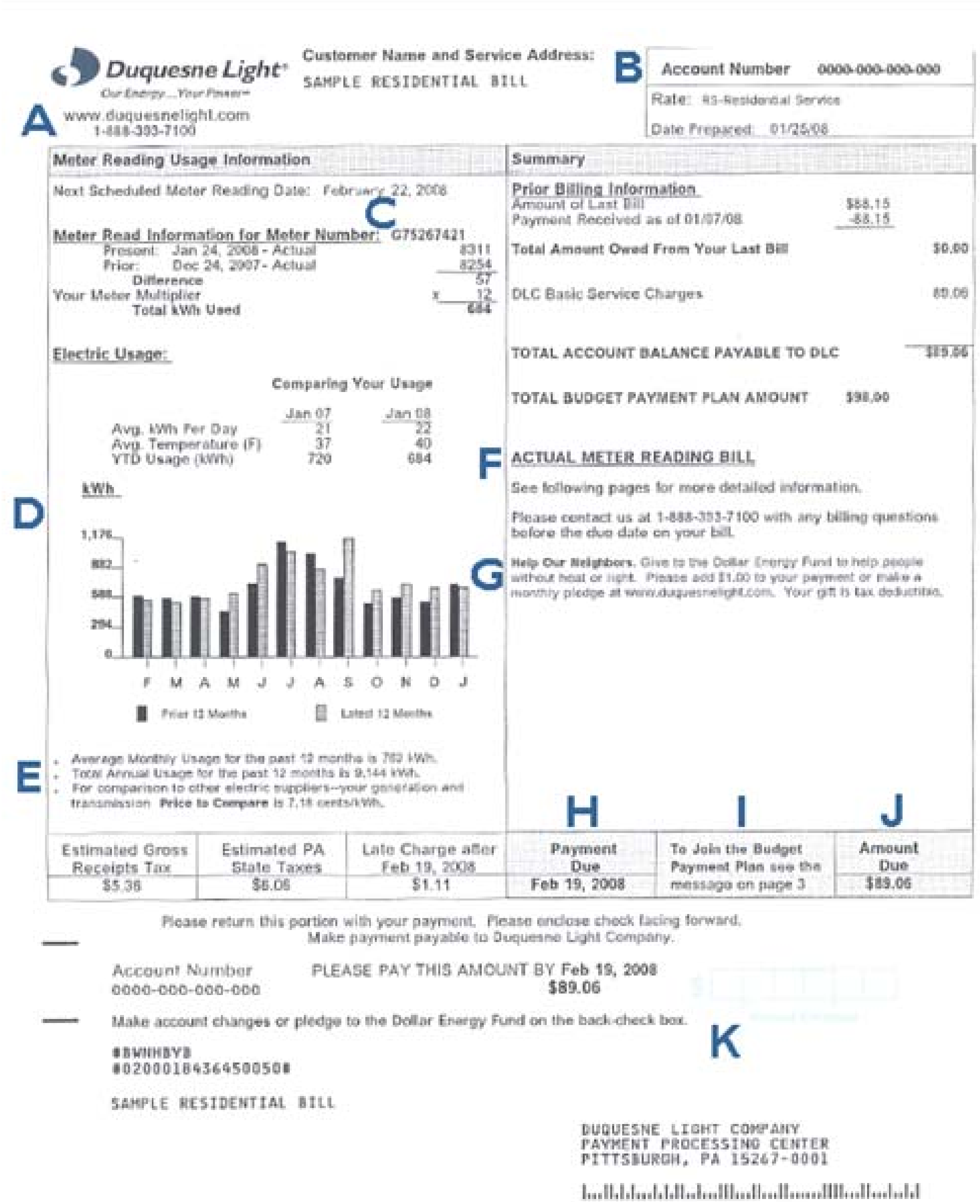
Motivation

- For the construction industry:
  - How green are green buildings?
  - Car manufacturers required to provide MPG, why different for buildings?

Motivation

- For users/owners of buildings:
  - You can not control what you do not measure
  - Grocery shopping analogy



Duquesne Light
Our Energy...Your Power
www.duquesnelight.com
1-888-393-7100

Customer Name and Service Address:
SAMPLE RESIDENTIAL BILL

Account Number 0000-000-000-000
Rate: RS-Residential Service
Date Prepared: 01/25/08

Meter Reading Usage Information

Next Scheduled Meter Reading Date: February 22, 2008

Meter Read Information for Meter Number: G75267421

Present:	Jan 24, 2008 - Actual	8311
Prior:	Dec 24, 2007 - Actual	8254
Difference		57
Your Meter Multiplier		x 12
Total kWh Used		684

Electric Usage:

Comparing Your Usage

	Jan 07	Jan 08
Avg. kWh Per Day	21	22
Avg. Temperature (F)	37	40
YTD Usage (kWh)	720	684

kWh
1,176
882
588
294
0
F M A M J J A S O N D J
Prior 12 Months
Latest 12 Months

- Average Monthly Usage for the past 12 months is 762 kWh.
- Total Annual Usage for the past 12 months is 9,144 kWh.
- For comparison to other electric suppliers—your generation and transmission Price to Compare is 7.18 cents/kWh.

Summary

Prior Billing Information

Amount of Last Bill	$88.15
Payment Received as of 01/07/08	-88.15
Total Amount Owed From Your Last Bill	$0.00
DLC Basic Service Charges	89.06
TOTAL ACCOUNT BALANCE PAYABLE TO DLC	$89.06
TOTAL BUDGET PAYMENT PLAN AMOUNT	$98.00

ACTUAL METER READING BILL

See following pages for more detailed information.

Please contact us at 1-888-393-7100 with any billing questions before the due date on your bill.

Help Our Neighbors. Give to the Dollar Energy Fund to help people without heat or light. Please add $1.00 to your payment or make a monthly pledge at www.duquesnelight.com. Your gift is tax deductible.

Estimated Gross Receipts Tax	Estimated PA State Taxes	Late Charge after Feb 19, 2008	Payment Due	To Join the Budget Payment Plan see the message on page 3	Amount Due
$5.38	$6.05	$1.11	Feb 19, 2008		$89.06

Please return this portion with your payment. Please enclose check facing forward.
Make payment payable to Duquesne Light Company.

Account Number 0000-000-000-000
PLEASE PAY THIS AMOUNT BY Feb 19, 2008 $89.06

Make account changes or pledge to the Dollar Energy Fund on the back-check box.

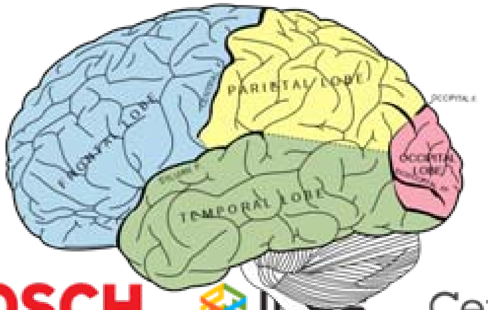
#BWNHBYB
#02000184364500508

SAMPLE RESIDENTIAL BILL

DUQUESNE LIGHT COMPANY
PAYMENT PROCESSING CENTER
PITTSBURGH, PA 15267-0001

Vision

- Energy-aware Smart Facilities
  - Aware: continuous monitoring, reporting.
  - Smart: user feedback with actionable information, able to predict, linking cause and effect: really smart.



Problem Definition

- Low feedback rate:
  - Monthly bill
  - Daily averages
- Difficult to obtain better data:
  - Hardware installation difficulties
  - Price:
    - Plug-through meters (~$100/each)
    - Circuit-level meters (~$3000/panel)

- Even if consumers had the data:
  - Analyzing it is cumbersome
  - Recommendations, forecasting should be automatic

Proposed Approach

- Non-intrusive load monitoring (NILM):
  - Obtain inexpensive measurements of total power consumption.
  - Use signal processing and machine learning techniques to disaggregate total load into individual appliances.
- Leverage existing infrastructure:
  - Electric circuits as communication medium between appliances and system.
  - Correlate with other sensor data: light intensity sensors, temperature, etc.
- More intelligent, less expensive solutions.

Previous Work

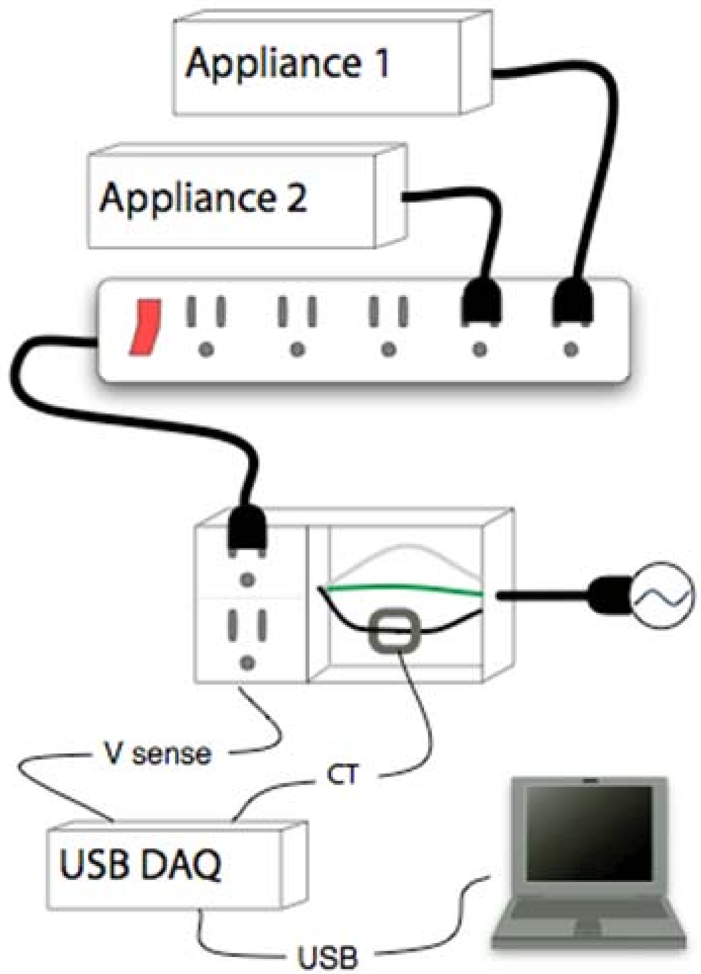
- NILM has been around for 20+ years.
- Very promising results in:
  - Controlled laboratory settings
  - Shipboard systems
  - Detecting large, quasi-static loads.
  - Typical residential buildings of the early 90's (no variable loads).
- One commercial product marketed for electric utilities.

- Our contributions:
  - Real world scenarios, in currently occupied buildings.
  - Interested in the applications of the disaggregated data.
  - Applying current Machine Learning techniques.

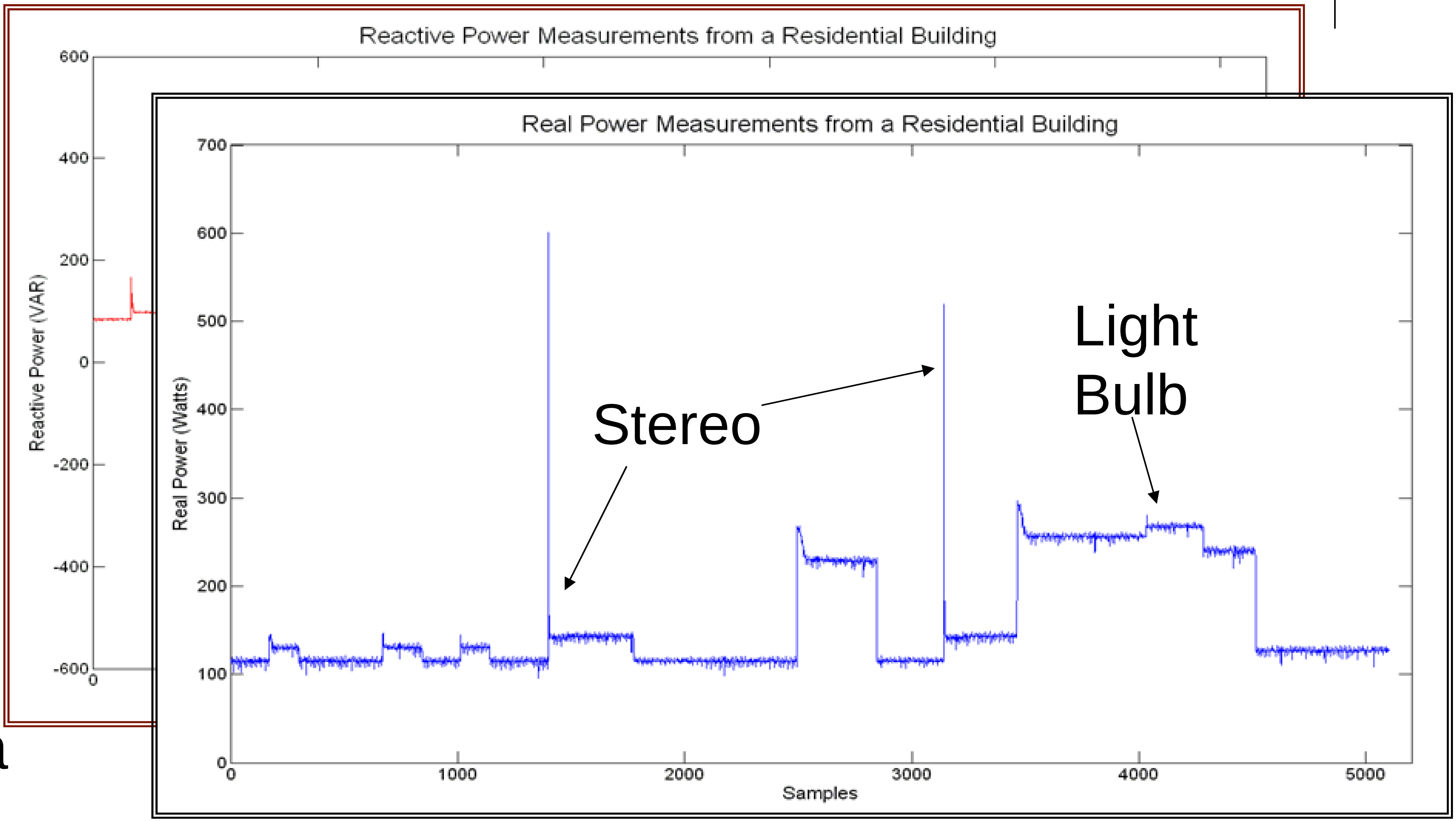
Our approach to NILM in detail...

The Hardware

- Incoming signals:
  - Aggregate Voltage and Current.
- Data Acquisition card (DAQ) converts analog to digital signals.
- Computer processes the raw waveforms and computes aggregate power metrics: real power (P), reactive power (Q), etc.
- Event detection and classification algorithms use this data.



The obtained signals



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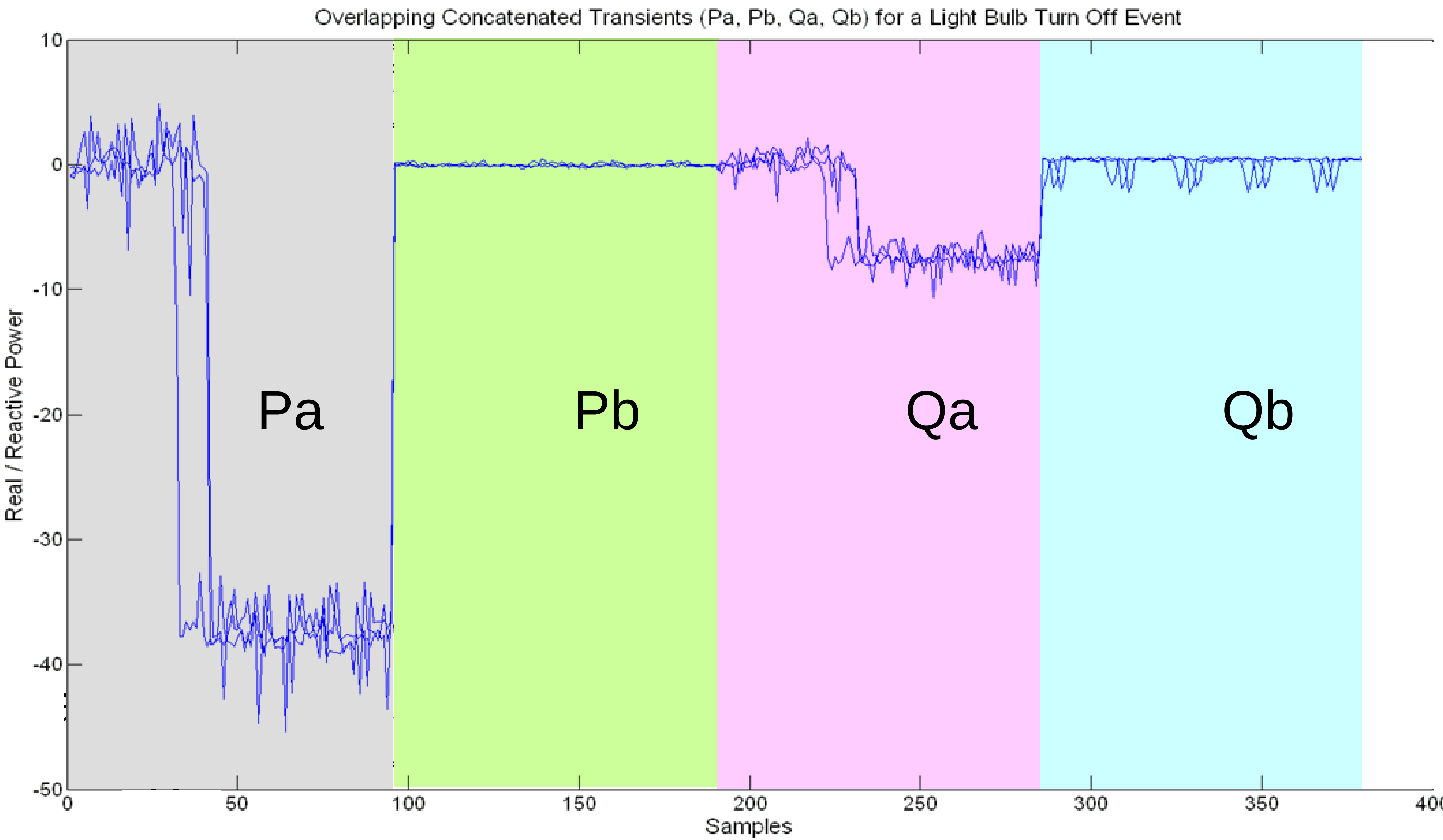
Event Detection

- Probabilistic approach
  - Generalized Likelihood Ratio

$$\text{possible\_event} = \arg\max_{l \le j \le k} \sum_{i=j}^{k} \ln \frac{P(x_i^1 \mid \mu_{after}, \sigma_{after})}{P(x_i^1 \mid \mu_{before}, \sigma_{before})}$$

- Currently testing wavelets

Event Classification: Feature Extraction



Event Classification: Feature Extraction

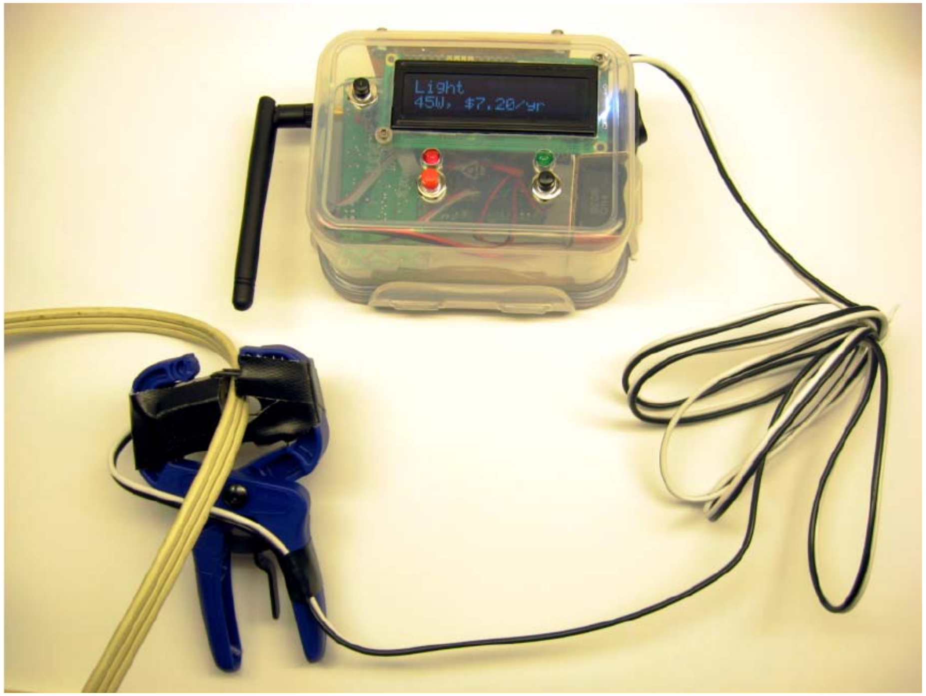
- Three methods:
  - Delta metrics: difference between pre/post average
  - Transient profile: all data-points in pre/post windows
  - Ridge Regression coefficients:
    - Polynomial basis: 1st order, no bias-term, proved best.
    - Gaussian Radial Basis Functions: 6 or 7 RBFs were enough
    - Fourier basis: 1 or 2 coef. proved best

Event Classification: Training Classifiers

- Two different setups:
  - 17 appliances in an occupied residential building (Real World)
  - 8 appliances in a laboratory (Noise Free)
- Four different classifiers:
  - Gaussian Naïve Bayes
  - 1-Nearest Neighbor
  - AdaBoost
  - Decision Trees

Event Classification: Training Classifiers

- WireSpy: a tool to support the training process.
  - Clamps around the appliance's wire.
  - Detects changes in the overall current draw.
  - Time-stamps those changes and sends this info. to the system wirelessly.
  - We obtain accurate ground truth.



Event Classification: Training Results

- **k-Nearest Neighbors (kNN)**
  - NF – 90% (RBF Coef.), RW – 81% (RBF Coef.)
- Gaussian Naïve Bayes (GNB)
  - NF – 83% (Delta), RW – 57% (Poly. Coef.)
- AdaBoost
  - NF – 76% (Poly. Coef.), RW – 0.50% (Poly. Coef.)
- Decision Trees
  - NF – 85% (Delta), RW – 58% (RBF Coef.)

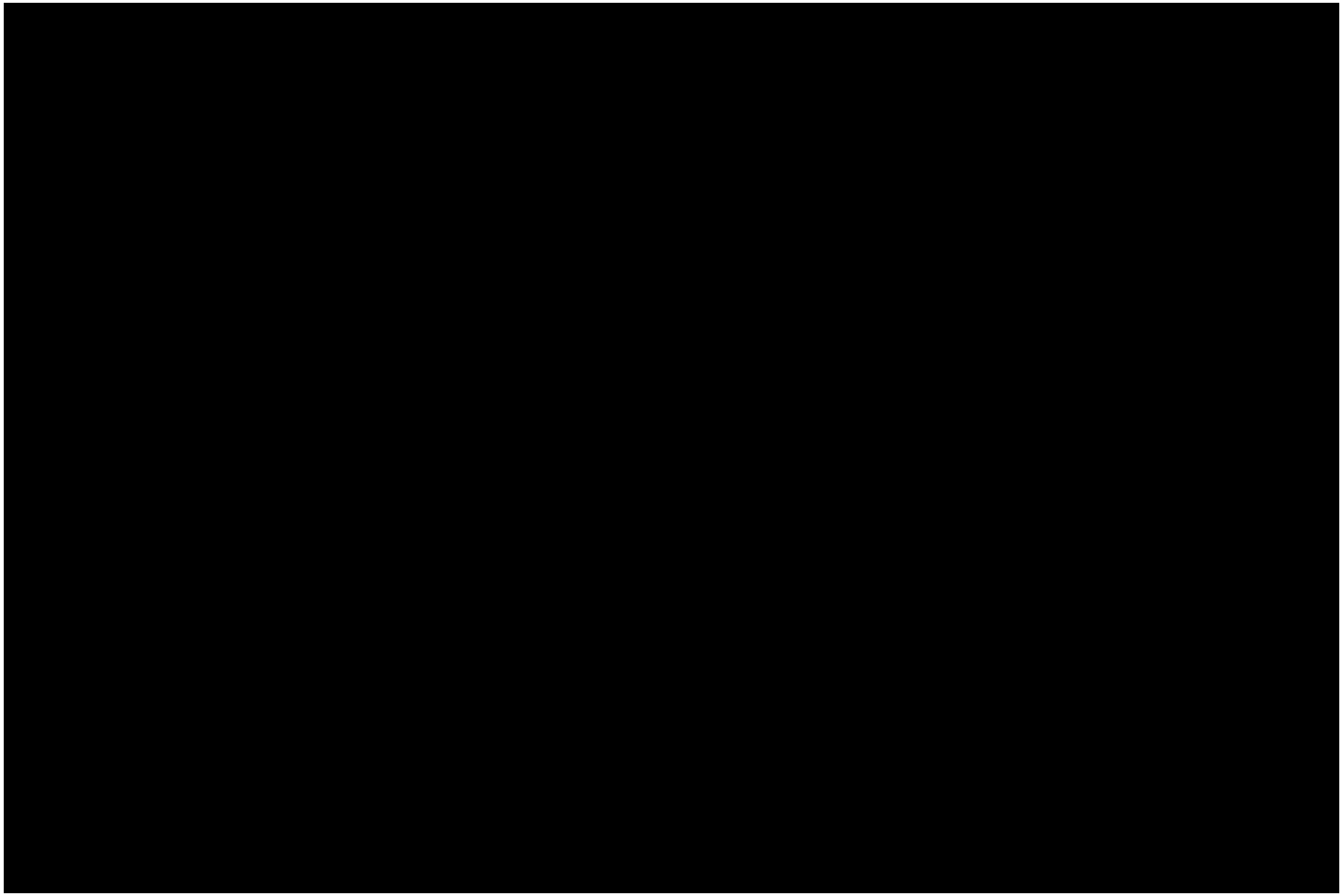
Event Classification: Validation Results

Validation Results (Accuracy in %)		GNB	kNN, k=1	Ada Boost	DT
Noise Free	Delta	52.94	67.65	**51.52**	61.76
	Whole Transient	38.24	73.53	--	58.82
	Polynomial Coefficients	58.82	67.65	**51.52**	52.94
	Fourier Coefficients	64.71	**79.41**	2.94	**64.71**
	RBF Coefficients	**67.65**	67.65	**	**64.71**
Real World	Delta	47.69	73.81	36.59	42.86
	Whole Transient	9.52	73.81	--	47.62
	Polynomial Coefficients	**61.90**	**80.95**	**61.90**	**57.14**
	Fourier Coefficients	50.00	**80.95**	55.00	54.76
	RBF Coefficients	47.62	76.19	35.71	54.76

Conclusions

- Very simple metrics and algorithms have a decent performance: slope and 1-NN.
- Our algorithms maintain their performance in noisy environments (real world).
- Facilities with this kind of system can obtain a detailed report with the operational schedule of all appliances.
- Future work includes adding other existing sources of information to correlate with: environmental sensors, time of day, etc.

Video Demonstration



Questions?

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